

School of Computer Science

Machine Learning in Fulfilment of

SPEC9270

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Declaration of Ownership: I declare that the attached work is entirely my own and that all sources have been acknowledged: 🗹

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Definition of problem – Kaggle Contest Entered

The Kaggle contest entered is the **MLSP 2014 Schizophrenia Classification Challenge** (Network, 2014), although the competition is over it is still possible to submit work and receive an evaluation. My reasoning for picking this competition is that I wanted to study psychology and go into research particularly in dissociative disorders and schizophrenia, however due to personal circumstances at the time I went with engineering. Data provided are two sets of multimodal features derived from MRI images. Two modalities are used to obtain said features, functional and structural MRI.

Today, I’m still interested in a PhD and have gained a different perspective I otherwise wouldn’t have had, one that sees that there are a lot of holes and short comings in traditional diagnosis of mental disorders such as D.I.D and schizophrenia. All of which hopefully can be dealt with machine learning (ML).

Some of these short comings are that there is no process to date that properly diagnoses D.I.D, despite it being acknowledged as a mental illness in the 1950s, research between then and now has been done but was later found to be fraudulent or difficult to reproduce. (David Blihar, 2020)

While remaining brief and acknowledging other issues that stem from the use of machine learning (ML), MRI and fMRI images can be fed to ML algorithms in order to be used as a tool that can help clinicians avoid misdiagnosis. Young girls tend to not be diagnosed with ADHD because it manifests differently (CONNOLLY, 2020), having a better system for such differences in mental health would help avoid undiagnosed patients in situations such as school performance.

Currently the best/popular go to method is MRI image classification as they are interpretable by clinicians and can be examined after a ML model points to one claiming “that one there seems off”, this is temporary solution to deep learning techniques being powerful for classification yet uninterpretable which is a huge deficit for application in healthcare. This is why, currently, I think ML will be another tool for diagnosis not a replacement or augmentation of existing methods.

Having said that, there are other areas such as using NLP for diagnosing/detecting the onset of Alzheimer’s disease (Elif Eyigoza, 2020).

This is where I want to step in, I want to spend time to develop skills and knowledge in machine learning, leveraging my engineering experience in order to transition into ML in mental health, an area my workplace (IBM) is active in.

This project hopefully will be an introduction to that, the dataset used in this project is in a different format then what I expected, I approach it as a learning opportunity for the future.

Models Built – Model Configuration

**Data preparation**

There was very little required to prepare data for this assignment on the surface level. Originally, I was under the impression that the data consisted of MRI images, however it’s a set of correlation values and other extracted multimodal features derived from MRI scans. Datasets were combined to form one in an attempt to encompass correlation between features during feature selection.

There are no missing or incomplete records in this dataset otherwise they would need to be removed or filled in if possible. There is an option to use a scalar to reduce gaps between values however these values are already very small and close together, from running models with and without the use of scalars it has made little to no difference.

Using visualisations to see the distribution of data and a boxplot to get a five-number summary for a quick evaluation could also be used, but in the current state of this assignment there wouldn’t be much value of doing that.

The reasoning behind there being very little data preparation on the surface level is that this data set came in two files. Finding ways to better extract features would be a major To-do for future work, especially because some of these features can correlate with other illnesses

One way of working with MRI images when there is a shortage of data is to rotate them a few times to synthesis more data points for a machine learning algorithm to pick up on.

**Implementation**

**SVM/SVC**

The sigmoid kernel returns a binary value similarly to a logistic regression. The sigmoid kernel preformed best, to my limited understanding this is because it adds non-linearity when choosing which values to pass as an output and which one not to pass, if a result is > or equal to 0.51 it will round up to a 1 and likewise for 0 if its below 0.51. (Kumawat, 2019)

Following that I’ve created a loop in which the model is built without setting a random\_state. Once run it would select a model with the highest accuracy and store it in a variable, this loop was set to 100 iterations. If this variable is not set the models results will be different each time because a randomly seeded number will be chosen. The idea behind this was to brute force an optimal random\_state, however I was unable to then retrieve the number that was assigned to the model build call. I ended up settling for 104 as it preformed best from manual testing. I would use the same approach one would when using binary search, altering values and seeing the performance gains from the metrics described in the evaluation section.

**Random Forest**

The only parameter that was changed is the criterion, entropy was chosen because the information gain metric is a lot more valuable than the Gini index. Having said that, the performance difference currently is not big, ~2%. Other decision made when building this model is the use of a plot to show feature importance, however this was not fully implemented because of time constraints on my end. After trying and reading up on different params for each model iteration, other than the Gini index default configuration values seemed to work best.

**Linear Discriminant Analysis**

The reasoning behind using this model is that it has similar properties to SVM when using the sigmoid kernel, which has showed good results, at least when compared to other models. After trying and reading up on different params for each model iteration, the defaults seemed to work best.

Local Evaluation – Evaluation Strategy

When comparing models and reading what each leader board score is for, I found that the private leader board score is the one that uses more data and is more relevant for the actual performance of the model. (Park, 2012).

Model evaluation consisted of:

Accuracy 🡪 fraction of predictions the model got right.

Precision 🡪 Refers is a ration of correctly predicted positives to the total of predicted positive observations.

Recall 🡪 Meanwhile recall refers to the number of those instances that are correctly predicted.

Cohen’s Kappa 🡪 This is a metric used to assess percent agreement, this is a useful metric because it also takes into account the possibility of said agreement occurring by chance. (McHugh, 2012) This is accomplished by taking the difference between the overall accuracy and the overall accuracy that can be obtained by chance. This metric is used when working with unbalanced datasets. Its an informative way to if the dataset is unbalanced or not as unbalanced datasets will produce a lower value.

Log Loss/Cross-Entropy 🡪 measures the performance of a classification model, however it requires probability values rather than binary values, for the current setup this metric was not used buts its worth mentioning as it seems popular and useful for models where probability values can be used.

Learning Curve 🡪 This ‘metric’ or more so visualisation maps the change in performance as more values are added.

ROC 🡪 This is a graph that shows the performance of a classification model at all thresholds

AUC 🡪 This is a graph that visualises the are under the ROC curve, this can be interpreted as the probability that the model will rank a random positive example more highly than a negative example. It measures how well a prediction is ranked. (TAVISH SRIVASTAVA, 2019)

Usually for binary classification, precision, recall and F1 score should suffice. More metrics were used to get a better understanding of their application in classification models and they provide a better overview of the model itself.

K-fold Cross-Validation 🡪 data is partitioned into k number of subsamples; this is repeated k number of times and each time one of the subsets is used as the set/validation set meanwhile the k-1 subset is used to train the model.

Local Evaluation – Evaluation Results

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Model | Accuracy | Precision | Recall | F1 Score | Cohens Kappa | Kaggle private score | Learn-R pos or neg | AUC |
| SVM | 0.808 | 0.9 | 0.692 | 0.805 | 0.615 | 85.6% | 38- | 0.81 |
| RF | 0.808 | 0.8 | 0.727 | 0.8 | 0.601 | 74.6% | 0 | 0.71 |
| LDA | 0.769 | 0.833 | 0.714 | 0.769 | 0.541 | 82.8% | 80+ | 0.77 |

**SVM – Support Vector Machine** | **RF – Random Forest** | **LDA – Linear Discriminant Analysis**

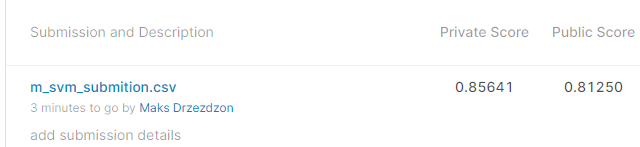
The best predictive metric of a model’s performance from the table above seems to be AUC derived from a ROC graph in the notebook. Other evaluation metrics for RF don’t seem to reflect the on Kaggle score however RF is not preferable when working with only two modalities, I hoped that because of the nature of the dataset it would preform better but it didn’t, having said that, feature selection was used but never properly implemented in a new model. SVM model excels at comparing two modalities.

Stepping to the LDA model, I think it was a step in the right direction, I wanted to explore other options for working with such a dataset and find alternatives that could outperform the SVM model. Unfortunately, I’ve ran out of time to do more work on this.

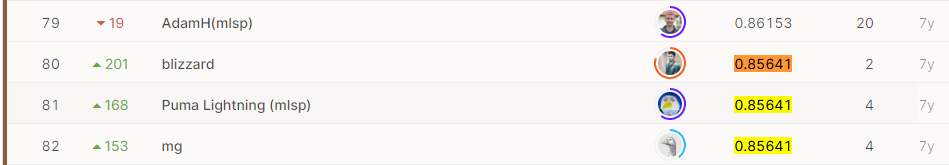
The **pos**itive or **neg**ative values for the **Learn-R**ate column stand for whether the model started performing better or worse with more data. RF had a constant value of 1, meanwhile SVM showed a sharp drop at 38 with LDA a strong progressive upward trend.

Kaggle – Performance Report

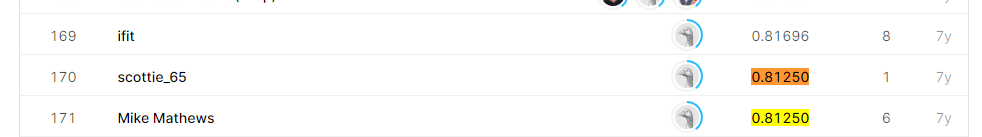
Best attempt with **support vector machine**:

**Public**: 170/313 **Private**: 80/313 - bronze

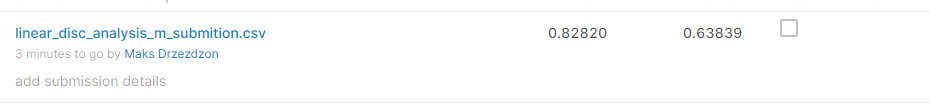
Private



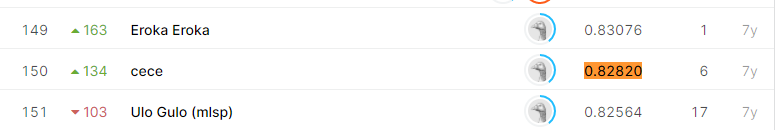
Public



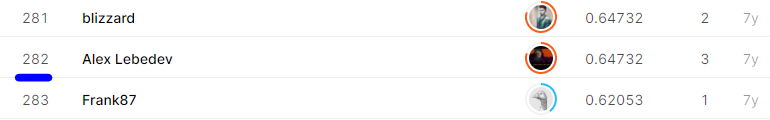
Best attempt with **discriminant linear analysis**:

**Public**: 283/313 **Private**: 150/313 

Private

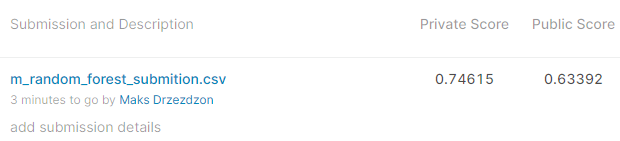


Public

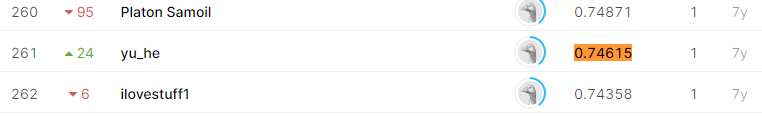


Best attempt with **random forest:**

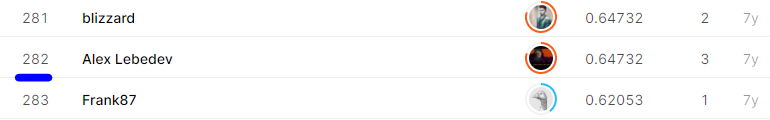
**Public**: 283/313 **Private**: 261/313



Private



Public



To-do’s – Further work

More time invested in understanding other methods of assessing model performances, similar to Cohens Kappa. Investigating other methods for handling multimodal data, along with allocating more time for feature selection. There is a lot of space for improvement which is something I’d how to achieve in my thesis using this dataset. Some methods to research later would be distance weighted discrimination function, other ways of using SVM, this can be accomplished by reading more research papers. Trying multi-layer neural networks using the previously used sigmoid function as an activation method. Id also like to reach out to the research facility and see what has come of that competition, have the models made by the winners been used, has there been any progress made since the?

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